The Whale Optimization Algorithm for Efficient PEM Fuel Cells Modeling

M. B. Danoune[1*], A. Djafour[1**], Yue Wang[2], A. Gougui[1]

[1]Faculté des Sciences Appliquées, Laboratoire LAGE, Université Kasdi Merbah Ouargla, Ouargla, Algérie

[2]Department of Engineering and Design, University of Chichester, Bognor Regis, PO21 1HR, United Kingdom

Abstract

Developing an accurate model is extremely important to design efficient proton exchange membrane fuel cells (PEMFCs) systems. The current work proposes the Whale Optimization Algorithm (WOA) for establishing an accurate and reliable PEMFC models. The idea is to increase accuracy of the extracted model parameters by minimizing error between the experimental and estimated polarization curves. WOA is utilized to mainly mitigate the effect of the local optimum stagnation and the premature convergence that appear with most of literature methods applied in this regard. The effectiveness of the WOA in modeling the PEMFC generators is demonstrated by the experiments using Heliocentris FC50 PEMFC test bench. In contrast to the existing works that characterized the behavior of the PEMFCs under fixed temperature values, the performance of developed model in providing accurate results is investigated under different operating conditions. The efficacy of the WOA is further checked using the data of two PEMFCs available in the literature, namely BCS-500W, and Ballard V. Moreover, a comparison is done with some challenging literature techniques along with the necessary statistical analysis. The final results prove that the WOA has very competitive performance. The proposed WOA has produced the lowest Mean Absolute Error among all tested methods, with values of 0.0589V, 0.2323V, and 0.2867V for Heliocentris FC 50, BCS, and Ballard fuel cells, respectively. Besides, the constructed Heliocentris FC 50 model yields highly accurate results, especially under varying temperature values. Owing to this, it can be stated that the WOA a powerful modeling tool. Therefore, it is highly recommended to be employed for creating high-quality PEMFC models.

Keywords: Hydrogen energy; PEMFC; PEMFC Modeling; WOA; Parameter identification.

*Corresponding author

** Corresponding author

E-mail:danoune.mohammed.bilal@gmail.com/danoune.m_bilal@univ-ouargla.dz (M.B. Danoune)

djafour.ah@univ-ouargla.dz (A. Djafour).

Symbols and abbreviations

ABC Artificial-bee-colony

DE Differential-evolution

FC fuel-cell

MAE Mean-absolute-error (V)

OF Objective-function (A)

PEMFC proton-exchange-membrane fuel-cell

PSO Particle-swarm-optimization

GA Genetic-algorithm

RE Renewable energy

RMSE Root-mean-square-error

WOA Whale-optimization-algorithm

SSD Sum of squared deviations

Max_it Maximum iterations

A Membrane area (cm^2)

$\vec{A}, \vec{a}, \vec{C}$ Constant coefficients

b Constant parameter (V)

C_{O2} Oxygen-concentration

$\vec{D}$ Distance between agents

E_{nernst} No-load voltage (V)

I Stack current (A)

i Iteration counter

J Stack current-density (A/cm^2)

J_{max} Maximum-current-density (A/cm^2)

l Membrane-thickness (cm)

N_s Number of cells collected in series

P_{H2} Hydrogen pressure (atm)

P_{O2} Oxygen pressure (atm)

P_{H2O} Water pressure (atm)

P_a Anode nominal pressure (atm)

P_c Cathode nominal pressure (atm)

RH_a Anode relative humidity

RH_c Cathode relative humidity

R_m **and** R_c Membrane and metal contact resistances (Ω)

$\vec{r}$ Random number [0-1]

T Stack temperature (K)

V_{act} Activation Voltage (V)

V_{con} Conductivity voltage (V)

V_{ohm} Ohmic-overpotential (V)

V/I Voltage-current points

$\vec{X}(i)$,$\vec{X}(i+1)$ Agent position and agent updated position

$\vec{X^*}(i)$ Best position/ Optimum-solution

GO Global-optimum

LO Local-optimum

ρ_M Membrane resistivity (Ωcm)

ξ_1, ξ_2, ξ_3, and ξ_4 Parametric coefficient (-)

λ The-quality-of water content (-)

β constant factor (V)

η Efficiency of the method (-)

OF_{min} Best objective function recorded during the experiment

$\overline{OF}$ Average value of the all recorded objective function values

1. Introduction

The growing environmental concerns, in addition to the rapid depletion of fossil fuel reserves have provoked many governments worldwide to invest more in renewable energy sources (RES)

[1]. Among available RES, wind and PV energies are envisaged as promising candidate solutions which can meet the present and future energy requirements with zero emissions [2-4]. However, the power provided from these two energy sources is intermittent due to weather variability [5-7]. An unexpected change in the environmental conditions can significantly affect the productivity of the such power sources [7, 8]. For instance, the generated power by PV arrays decreases as solar irradiance decreases, and it could even drop to zero in case of cloudy days [2]. Similarly, wind generators remain inactivated as long as the local wind speed is lower than the cut-in speed of the turbine [2]. The association of backup support systems like batteries and hydrogen storage becomes, therefore, necessary to maintain high reliability [9, 10].

Recently, hydrogen-based storage systems have received increasing interest from researchers, especially with the significant improvements in fuel cells (FCs). Many research works [10-12] consider that the combination of FCs along with other energy sources is an excellent option that can play a crucial role in achieving 100% reliability. Since its discovery in 1889 [13], FC has evolved remarkably over time, and it has been applied to a broad variety of areas in order to profit from its positive image. There are various commercial kinds of FCs available in the market [13]. Among them, PEMFC, which has gained the spotlights due its compact design, lightweight, solid electrolyte, low operating temperature, zero emissions, and high-efficiency [20, 21]. These valuable features have let the PEMFC horizon extend to many vital sectors including the transport domain [15, 16], distributed generation systems [17, 18], electronic industry [19], and other applications to replace fossil fuel-based energy generation systems. For proper design, analysis, and effective control of PEMFC systems, accurate modeling and simulation are required [12]. In this regards, the mathematical mode of Amphlett [22] is viewed as one of the most convenient models for predicting the outputs of the PEMFCs. This approach uses semi-empirical equations to evaluate the effect of various influencing factors such as stack temperature, humidity, and anode & cathodes pressures on the performance of the PEMFC, without examining in-depth the physical, thermal, and electrochemical phenomena involved in the system. However, before simulating the behavior of a specific PEMFC using Amphlett model, there are a number of unknown parameters that have to be accurately determined. These parameters are strongly coupled with each other, rendering the PEMFC parameter identification process a challenging task. Dozens of techniques have been proposed in the literature to appropriately identify the unknown parameters of the PEMFCs. These techniques can be split into two main categories, namely (i) traditional methods and (ii) meta-heuristic algorithms. The traditional methods like GRG [23], fractional-order model [24], impedance-spectroscopy [25], and impedance-characterization [26] can hardly define the model parameters effectively, since the system is highly nonlinear and has a large number of variables. Thus, to overcome the difficulties associated with the aforementioned techniques, meta-heuristic optimization methods have been applied.

Meta-heuristic methods are nature-inspired and population-based search techniques. They have an excellent ability to effectively resolve global-optimization problems [27]. They have been successfully applied to solve a wide range of real-world problems [27-31], including parameter identification tasks. A comprehensive literature review showed that a good number of meta-heuristic methods have been applied in the context of PEMFC modeling. Ohenoja et al. [32] in 2010 proposed the genetic-algorithm (GA) to enhance the modeling of the PEMFC by fitting its model parameters with a set of experimental data. They analyzed the influence of parameter range on the performance of their proposed method. Their results indicated that the parameter boundaries employed need careful consideration. The same method (*i.e.,* GA) was hybridized with the Nelder–Mead search technique by Mo et al. [33] to improve its performance. They found that the hybridized GA performed more efficiently compared to the original GA, especially for steady state conditions. The cuckoo-search-algorithm, on the other hand, was combined with the adaptive explosion operator strategy to maintain the diversity of the individuals all over the search space [34]. Their numerical results proved that the proposed method by them has better performance regarding convergence and accuracy. Likewise, Chenget al. [35] have analyzed the performance of the Differential-Evolution (DE) method in the process of PEMFC parameters extraction. The effectiveness and robustness of their proposed method were compared with other competitive literature approaches. Their results showed that among all tested methods, the DE has a great flexibility in avoiding local optimum stagnation and extracting accurate results. The work done in Ref. [36] was similar to this study in some aspects. However, the data used in the this article is extracted from different FCs and under else operating conditions. Also, many of the aforementioned works have studied the performance of their PEMFC under fixed temperature values. However, in this paper we consider the output voltage of the system under varying temperature values. Moreover, the behavior of particle-swarm-optimization (PSO) algorithm was discussed by Ye et al. [37]. They compared the results with some traditional optimization methods and found that the PSO is an effective approach for defining the parameters of the PEMFC even if the data is noisy, or the set initial boundaries have a broad range. Menesy et al. [38] applied the Chaotic Harris Hawks optimization for estimating the accurate operating parameters of four commercial PEMFCs. This method is new and it is being increasingly used in various applications to solve their optimization problems. The authors in the above-said study tested the stability and reliability of the method in comparison with some existing optimization techniques. Their method has showed good performance in developed reliable PEMFC models. Sultan et al. [39] proposed an improved salp swarm algorithm to reduce the local optimum trapping behavior when optimizing the parameters. They validated the effectiveness of the new method in modeling the PEMFC using statistical benchmarks. Their simulation results proved the stability and reliability of method. Recognizing the advantages of heuristic modeling techniques, many additional methods have been applied in this regard, some of which are: seeker-optimization algorithm [14], P system based optimization algorithm [21], salp-swarm optimizer [15], harmony search [40], bird mating optimizer [41], grasshopper optimizer [42], grey-wolf optimizer [43], flower pollination [44], manta-rays optimizer [45], neural-network optimizer [46], atom-search [47], hybrid adaptive DE [48], and artificial-bee-colony (ABC) [49], improved TLBO method [50], biogeography algorithm [51], backtracking search algorithm [52].

With regards to the above literature review, it is apparent that considerable efforts have been undertaken to improve the PEMFC modeling through the use of various optimization methods. However, there are some opportunities to attempts new algorithms, since the meta-heuristic optimization domain is still evolving over time. In addition to that, and apart from the promising results attain in this regard, the no-free-lunch theorem made a precise remark that it is always beneficial to try out different/new optimization techniques when solving engineering problems. Because one method can be useful in solving one set of problems, but not necessarily effective with other sets of problems [53]. In other words, there still room to propose other methods and achieve further enhancements. For these reasons, the authors have the motivation to apply the Whale Optimization Algorithm (WOA) for improving the modeling of the PEMFCs.

The WOA is a new generation heuristic optimization method. It was proposed in 2016 by Mirjalili [54] to simulate the social behavior of humpback whales. The method has revealed superiority in solving complex engineering problems, for instance identifying the undefined parameters of the solar PV cells [55], dispatching the reactive power of the grid [56], sizing renewable systems [57], and forecasting regional wind speeds [58]. As such, the WOA is implemented in the present work in an attempt to improve the modeling of the PEMFCs, and its efficacy is investigated in detail.

The aim this paper is to develop a high-quality model for PEMFCs by increasing accuracy of the extracted model parameters. The efficacy of the WOA is tested in three PEMFC case studies. For a fair comparison, the performance of the proposed method has been tested against that of various state-of-art algorithms. The major contributions, and the significant difference between this work and previous studies are illustrated in the following points:

(i) An accurate, reliable, and low-cost PEMFC simulation model for Heliocentris-FC50 PEMFC has been developed.

(ii) In contrast to the approaches employed in the existing works, which are difficult to program due to their complexity, a simple, and efficient stochastic search algorithm is proposed to determine the unknown parameters of the PEMFC.

(iii) Application of WOA method is proposed to mitigate the issues of local optimum stagnation as well as premature convergence. The method generates high degree of randomness so that the population is distributed all over the space, thus, the chance of getting trapped in one of local optimums is minimized.

(iv) Unlike the previous work performed by El-Fergany [36], which was similar to this paper in some extent, in this study, the effects of temperature variability on the performance of the developed model by WOA is investigated in depth.

The rest of the article is organized as follows: Section (2-3) defines the mathematical model of the tested FCs and formulate the objective function. Section (4) explains the optimization procedure in detail using the WOA algorithm. Sections (5-6) analyzes and discusses the outcomes of the work. Finally, Section (7) summarizes the key outcomes of the paper and outlines the future works.

2. PEMFC mathematical model

A typical PEMFC is depicted in Fig. 1. The electrochemical generator consists of three main elements, which are: a solid membrane (often Nafion^{TM} material) and two metallic plates called anode and cathode. These last mentioned are the places where hydrogen and oxygen react, respectively [13]. Hydrogen atoms split into electrons and protons to generate an electrical current when an external load is connected. Also, the device releases heat and water steam as products of these electrochemical reactions. The overall equation that evaluates the output voltage produced by the stack is given in Eq.(1) [15]:

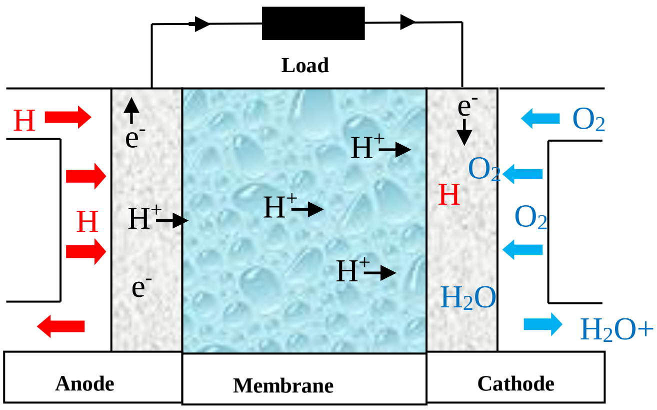

Fig.1- Inner view of PEMFC

$$V = N_s \times [E_{nernst} - V_{act} - V_{con} - V_{ohm}] \quad (1)$$

$$V = N_s\times\begin{bmatrix}\{1.229\text{-}0.85\times10^{-3}\times(T\text{-}298.15)+4.3085\times10^{-5}\times T\times\ln\left(P_{H2}\times\sqrt{P_{O2}}\right)\}\\ +\{[\xi_1+\xi_2\times T+\xi_3\times T\times\ln(C_{O2})+\xi_4\times T\times\ln(I)]\}\\ +\{\beta\times\ln(1-J/J_{max})\}\text{-}\{(R_m+R_c)\times I\}\end{bmatrix} \tag{2}$$

Where, V is the output voltage of the PEMFC generator, and Ns is the number of cells assembled in series. E_{nernst} is the no-load voltage in an open circuit thermodynamic balance. V_{act} is the activation voltage resulted from the sluggish kinetics reactions taken place on the surface of the anode and cathode. V_{con} is the concentration voltage drop. V_{ohm} is the ohmic voltage drop caused by the resistance of membrane and metal contacts, $R_m(\Omega)$ and $R_c(\Omega)$. T is the cell temperature (K), and ξ_1-ξ_4 are semi-coefficients based on electrochemistry. P_{H2} and P_{O2} are the hydrogen and oxygen partial pressures (atm) enters the anode and cathode, respectively. I and J are the current (A) and current density (A/cm) of the PEMFC stack, respectively. C_{O2} is the concentration of oxygen on the surface of catalysis (mol/cm^3). β is an empirical parametric coefficient in volts. J_{max} is the maximum allowable currently density. The concentration C_{O2} and resistance R_m calculated using Eq.(3) and Eq.(4), respectively [12, 13, 35, 44]:

$$C_{O2}=\frac{P_{O2}}{5.08\times10^{6}}\times\exp^{(498/T)} \tag{3}$$

$$R_m=\frac{l\times\rho_M}{A}=\frac{181.6\left[1+0.03\left(\frac{I}{A}\right)+0.062\left(\frac{T}{303}\right)^2\left(\frac{I}{A}\right)^{2.5}\right]\times l}{A\times\left[\lambda\text{-}0.634\text{-}3\times\left(\frac{I}{A}\right)\right]\times\exp[4.18(\frac{T\text{-}303}{T})]\times A} \tag{4}$$

ρ_M stands for the resistivity of membrane (Ωcm), and l is the thickness of membrane (cm). A is the activation surface of stack (cm^2), and λ is an adjustable fitting parameter influenced by the material properties of membrane [15, 44].

Furthermore, the pressures P_{H2} and P_{O2} can be determined by Eq.(5) and Eq.(6), respectively:

$$P_{H2}=0.5\times RH_a\times P^*_{H2O}\times\left[\left\{\exp\left(\frac{1.635\times(I/A)}{T^{1.334}}\right)\times\left(\frac{RH_a\times P^*_{H2O}}{P_a}\right)\right\}^{-1}\text{-}1\right] \tag{5}$$

$$P_{O2}=RH_c\times P^*_{H2O}\times\left[\left\{\exp\left(\frac{4.192\times(I/A)}{T^{1.334}}\right)\times\left(\frac{RH_c\times P^*_{H2O}}{P_c}\right)\right\}^{-1}\text{-}1\right] \tag{6}$$

$$\log_{10}(P^*_{H2O})=2.95\times10^{-2}\times(T\text{-}273.15)\text{-}9.18\times10^{-5}\times(T\text{-}273.15)^2+1.44\times10^{-7}\times(T\text{-}273.15)^3\text{-}2.1 \tag{7}$$

Here P^*_{H2O} is the water pressure in atm, which can be calculated by Eq.(7). While, RH_a and RH_c are the relative humidity's at the surface of the anode and cathode, respectively. P_a and P_c are the inlet pressures of anode-cathode, respectively[12, 44].

3. Objective function

In the equivalent model of the PEMFC given above, several parameters must be determined. The constants Ns, A and l are known and can be found in the manufacturer datasheet. Also, the quantities T, P_{H2} and P_{O2} can be measured during the experiment, while the remaining unknown parameters *i.e.*, ξ_1, ξ_2, ξ_3, ξ_4, λ, β, R_C & J_{max} largely depend on the status of PEMFC, and they require parameters fitting using an optimization method.

To ensure an accurate estimation of the above-mentioned parameters, we need to change the problem into an optimization task. An objective function (OF) should be created to minimize the error between the true and estimated polarization curves. The unknown parameters are set as decision variables to be then tuned until a good matching is obtained. In this study, the Mean Absolute Error (MAE) between the experimental and output model voltages is defined as an OF, which can be written as follows:

$$OF\left(V_{exp}, I_{exp}, x\right) = MAE = \frac{\sum_{k=1}^{N}\left|V_{exp}(k)-V_{est}(k)\right|}{N} \tag{8}$$

Where, x= [ξ_1, ξ_2, ξ_3, ξ_4, λ, β, R_C & J_{max}] is the parameter vector to be tuned. $V_{exp}(k)$ and $V_{est}(k)$ are the k^{th} experimental and estimated voltages, respectively. N is the number of samples contained in the k^{th} group. Moreover, worth mentioning that the unknown parameters were bounded according ti the values in Table 1.

Table 1– Parameter boundaries [46]

Parameter	Lower-bound	Upper-bound
ξ_1	-1.1997	-0.8532
ξ_2	1.0000E-3	5.0000E-3
ξ_3	3.6000E-5	9.8000E-5
ξ_4	-26.000àE-5	-9.5400E-5
λ	13	23
β	0.0136	0.5000
R_c	0.1000E-3	0.8000E-3
J_{max}	0.4000	0.5000

4. Principle of the WOA

The WOA is a probabilistic and population-based search method. It was proposed in 2016 by Seyedali [54] to simulate the social-behavior of humpback-whales. The technique has been successfully applied in many engineering problems, since it is efficient in locating the global-optimum, easy to program, and requires few controlling parameters. The optimization procedure is conducted by three main steps as described above [54]:

4.1. Encircling the prey

This step is important for predicting the potential position of the prey. Since food position is unknown at the beginning for predators, the best agent $\overrightarrow{X^*}$ in the swarm is taken as the target and the distance between any agent and the best agent is calculated by Eq.(9). The remaining particles now must follow the best agent as expressed in Eq.(10). Here, $\overrightarrow{X^*}$ should be adjusted at every-iteration if there is a better solution.

$$\vec{D}=\left|\vec{C}.\overrightarrow{X^*}-\vec{X}(i)\right| \tag{9}$$

$$\vec{X}(i+1)=\overrightarrow{X^*}-\vec{A}.\vec{D} \tag{10}$$

Where, $\overrightarrow{X^*}$ is the best agent found so far and $\vec{X}(i+1)$ is the updated position vector. $\vec{D}$ represents the distance vector between the agents and best position. $\vec{A}$ and $\vec{C}$ areconstant vectors, which can be calculated by using Eq.(11)-Eq.(12) respectively.

$$\vec{A} = 2.\vec{a}.\vec{r} - \vec{a} \tag{11}$$

$$\vec{C}=2\vec{r} \tag{12}$$

Where, $\vec{a}$ is a linear decreasing number from 2→0 over-the-course of iterations, and(r) is a random value that lies in ∈ $0 \leq r \leq 1.0$.

4.2. Bubble net attacking

Humpback whales have special hunting mechanism called bubble-net feeding. It was noticed that the foraging process is done by generating special bubbles along ‘9’shaped path. This behavior could be simulated by using Eq.(13):

$$\vec{X}(i+1)=\begin{cases}\overrightarrow{X^*}-\vec{A}\times\vec{D} & \text{if } p<0.5\\ \overrightarrow{D'}\times e^{b\times l}\times\cos(2\pi\times l)+\overrightarrow{X^*} & \text{if } p\geqslant 0.5\end{cases} \tag{13}$$

Where, p is a random numeric ∈[0,1], $\overrightarrow{D'}$ is the distance-between current whale and best solution as defined in Eq.(9). Moreover, b is a fixed digit (b=1.0), and l is a random number that lies in-

$1.0 \le l \le 1.0$. It is worth noting that if p in Eq.(13) is greater than 0.5 a spiral equation is launched to simulate the '9'shape motion.

4.3. Seeking for the prey

In the WOA search method, all agents must contribute to the search process. To make sure that a global search is performed in all space, the agents are forced to move far-off the reference whale as described mathematically in Eq.(15).

$$\vec{D}=\left|\vec{C}.\overrightarrow{X_{rand}}(i)-\vec{X}(i)\right| \tag{14}$$

$$\vec{X}(i+1)=\overrightarrow{X_{rand}}(i)-\vec{A}.\vec{D} \tag{15}$$

Where, $\overrightarrow{X_{rand}}(i)$ is position, which randomly taken from the current swarm. A pseudo-code for WOA is introduced below to minimize method.

Algorithm1. Pseudo code for WOA algorithm [54]

Initialize the whales population (1, 2, ..., total number)
Calculate the *OF* of the population by Eq. (12)
set $\overrightarrow{X^*}$ as the position corresponds to the minimum fitness (best fit)
while (Stop criteria is not met)
for each search agent
Update a, A, C, l, and p
if1 ($p<0.5$)
if2 ($|A| < 1$)
Update the current agent using Eq. (10)
else if2 ($|A|\geq 1$)
Choose a random agent (X_{rand})
Update the current agent using Eq. (15)
end if2
else if1 ($p \geq 0.5$)
Update the current agent using Eq. (13)
end if1
end for
If any agent goes out-of the search space rectify it
Compute the fitness of every agent
Update $\overrightarrow{X^*}$ if there is a better solution
end while
Go back to $\overrightarrow{X^*}$

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5. Experimental steps and analysis

As mentioned, the main goal of the study is to develop a low-cost, easy access, and reliable emulation model for Heliocentris-FC50 test bench installed in LAGE lab (Electrical engineering laboratory), Ouargla university. The platform is used to characterize, analyze, and validate the different control algorithms that ensures optimal operation of the PEMFC-based systems. As shown in Fig. 2, the test bench consists of a 40W PEMFC, hydrogen bottle (capacity of 225 liters, with 10 bar in nominal pressure), pneumatic valve, cooling fan, and programmable electronic load. In addition, the unit is equipped with a data acquisition station to monitor and store all the relevant information.

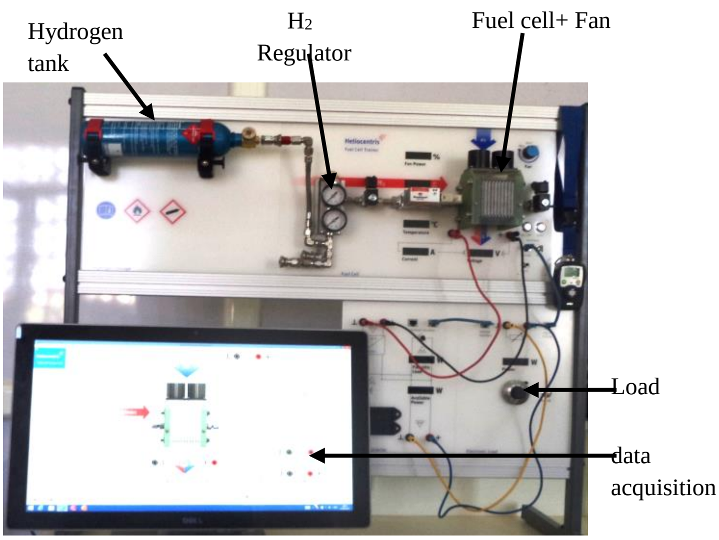

Fig. 2 - Experimental platform for Heliocentris FC50

Before addressing the set target, the performance of WOA with some of the FCs studied previously in the literature is examined. To be more specific, the data of BCS-500W and Ballard Mark V PEMFCs collected from [46, 60] have been used to investigate the efficacy of the WOA in defining the optimal model parameters, and then the method is used to establish the required model.

Moreover, for a fair study, a comparison has been done with some competing state-of-the-art methods, namely differential-evolution (DE) [35], particle-swarm-optimization(PSO) [37], and artificial-bee-colony (ABC) [49]. These algorithms have shown good performance in previous studies. Their control parameters were set as recommended in their original papers (see also Appendix 1). The developed code was executed 100 times, independently, during 1000 iterations. The best result among all candidate solutions was taken as the desired solution. Also, the number of agents were set equal to 50 in each evaluated algorithm. The computations were performed on one single computer with the following configuration: Name Intel (R) Core(TM) i77500 CPU. RAM: 8.0GB. Processing frequency: 2 GHz. Hard drive: 500 GB. Operating system: Software: MATLAB R2018a (Windows-10, 64bits).

Furthermore, since swarm-based search methods are random in nature, it is important to assess their stability and robustness using some statistical indicators. The Mean-Absolute-Error, StE, and method efficiency (η) , which are given in Eq. (8), Eq. (16), and Eq. (18), respectively are applied in this study to measure the significance difference between used methods [46, 60].

$$StE=\sqrt{SSD^2\text{-}MAE^2} \tag{16}$$

$$SSD=\sum_{k=1}^{N}\left[V_{exp}(k)\text{-}V_{est}(k)\right]^2 \tag{17}$$

$$\eta=\frac{OF_{min}}{\overline{OF}}\times 100 \tag{18}$$

$$\overline{OF}=\sum_{i=1}^{100} OF_i/100 \tag{19}$$

Where, $V_{exp}(k)$ and $V_{est}(k)$ are the experimental and estimated stack voltages, respectively. $\overline{OF}$ is the average-value of 100 computed objective-functions, and OF_{min} is the minimum OF among all computed ones. Here, the smaller the values of MAE and StE, the more robust the method is. Also, the closest the value of efficiency to 1, the better the method could perform.

5.1. Case of BCS-500W

Data for this generator were collected from Refs [46, 60]. The aforementioned PEMFC has a rated power of 500W, with 32 cells stacked in series. The maximum-current-density (J_{max}) is 0.469 A/cm, while the membrane thickness and the cell active area (A) are 178 µm and 64 cm^2, respectively. Moreover, the nominal anode & cathode pressures as well as temperature of this stack are 1 bar, 0.2095 bar, and 333K, successively. Based on the above, the WOA was implemented to define the appropriate parameters of the stack. The results can be found in Table 2.

Fig. 3 depicts the (I/V) curves generated from the WOA model together with experimental measurements. A very good matching is shown between the estimations & real data. The accuracy of WOA is evidenced by the generated MAE value, which is 0.0530 V. This value obtained by WOA is the smallest MAE value among all the studied methods, as Table 2 reveals.

The convergence speed of this stack is displayed in Fig. 4. It is observed that the WOA quickly converges to the steady state value, and its accuracy improves as the number of iterations increases. The optimum result was reached after merely 81 iterations. Moreover, the robustness as well as precision of the studied methods were assessed by computing the following statistical benchmarks: MAE, StE, and method efficiency. The outcomes are listed in Table 4. A closer look in Table 4 (first column) shows that the suggested WOA algorithm has outperformed the other methods with its low deviations as well as its high efficiency. These salient remarks also prove that the proposed WOA method is more robust, and more stable than others. ABC has ranked second, with error value of MAE=0.0543,StE=0.0888 and efficiency of 95.24%. Whereas, PSO and DE have ranked third, and fourth, respectively, with relatively considerable deviations.

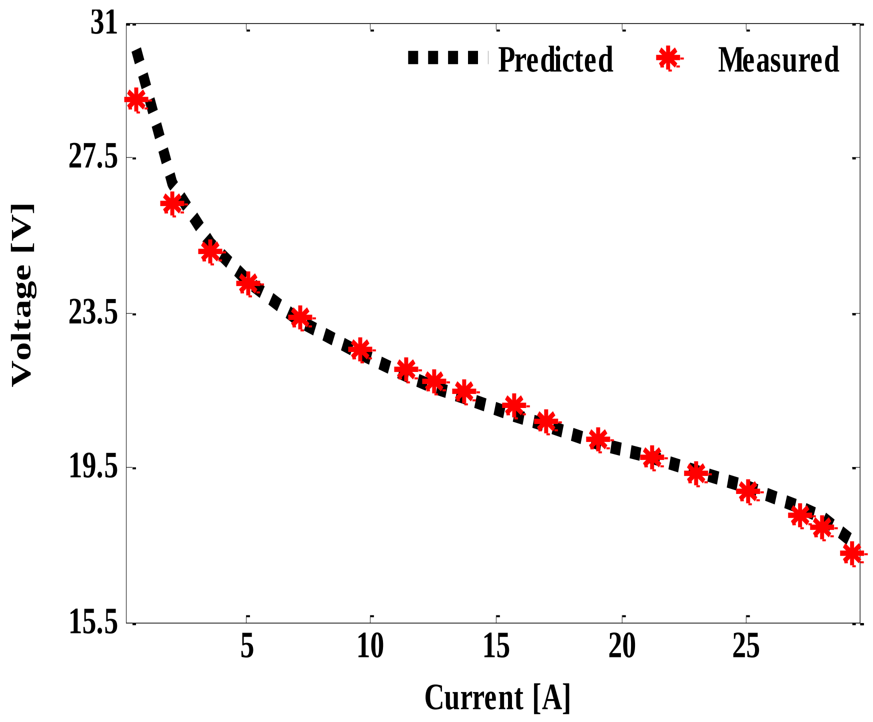

Fig. 3 – V/I plot of BCS-500W using WOA

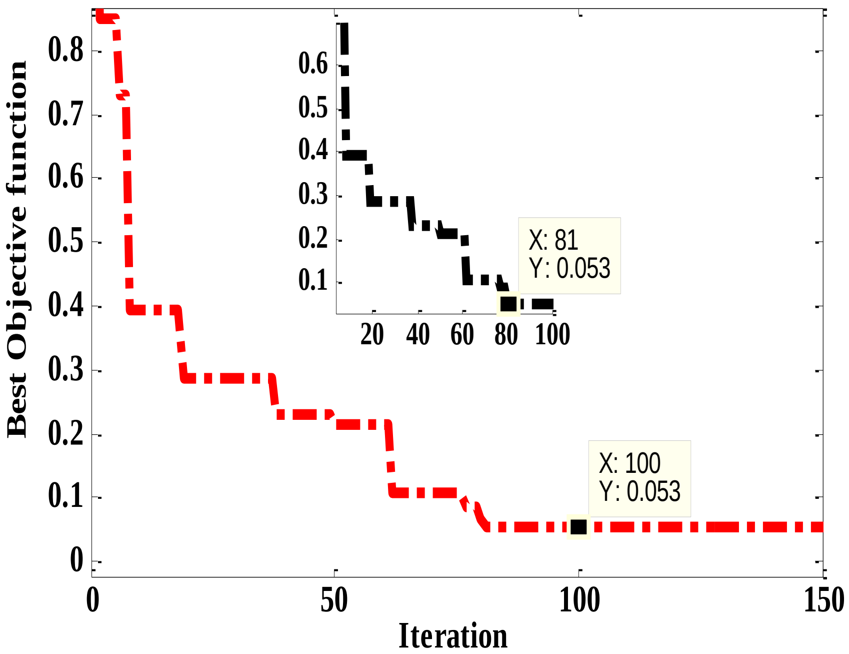

Fig 4–Convergence rate of BCS-500W V using WOA

5.2. Case of Ballard Mark V

In this section, a Ballard Mark V fuel cell, with the specifications listed below has been tested: rated power =5KW, cell area (A=50.6 cm^2), J_{max} (1.5 A/cm), Pa/Pc (1/1 atm), T (343K) [46, 60]. The extracted optimal parameters for this PEMFC are also summarized in Table 2. The obtained parameters were used to construct the (V/I) characteristic, as shown in Fig. 5. From Fig. 5, it is observed that the estimates of the WOA coincide considerably with the true (V/I) curves. The generated MAE value by the WOA is 0.1859 V, which is the lowest value among all. The convergence graph of this case study is depicted in Fig. 6. The WOA approach has converged rapidly. The best solution has been reached after only 52th cycles. In order to measure the accuracy and stability of WOA algorithm, the MAE, StE, and efficiency of this specific fuel-cell have been calculated again and displayed in Table 4 (second column). In this case, the error values obtained from all methods are close to each other. However, the WOA outcomes seems to be slightly better than those obtained by the approaches found in literature. The assessed statistical measures reveal the robustness of WOA again with this type of PEMFC.

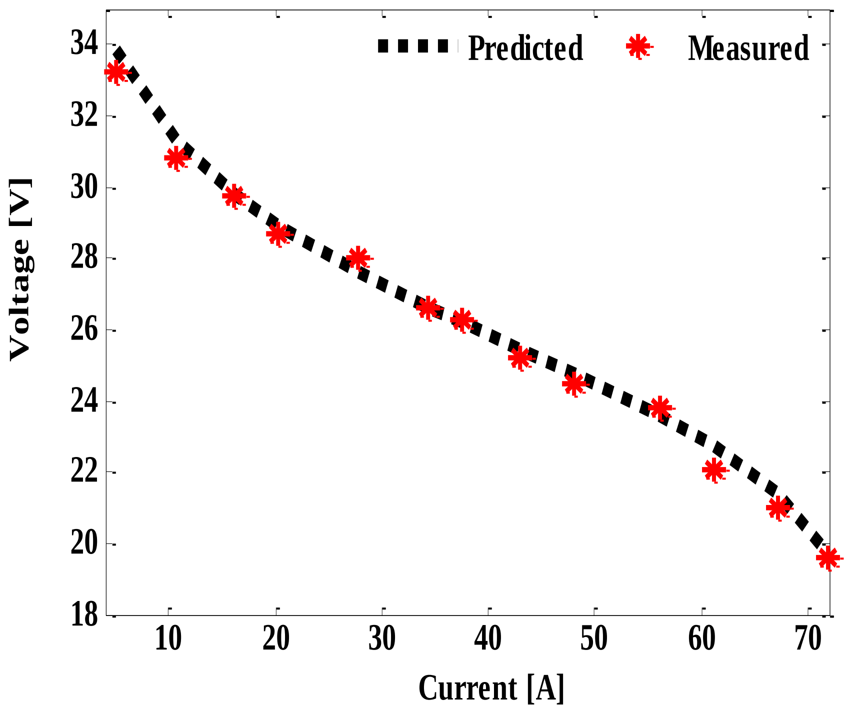

Fig 5 – V/I plot of Ballard Mark V using WOA

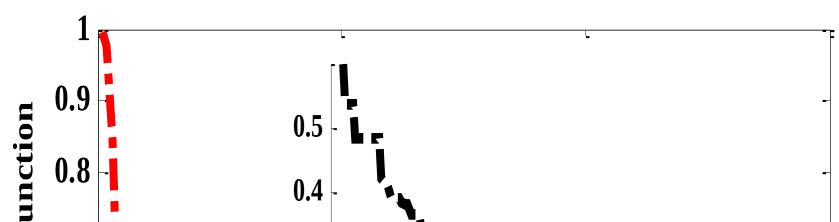

Fig 6 –Convergence rate of Ballard Mark V using WOA

Table 2 – Optimal parameters using WOA

Parameter	**BCS-500W**	**Ballard Mark V**	**Heliocentris**
ξ_1	-1.0823	-1.1515	-1.0837
ξ_2	0.0032	0.0038	0.0024
ξ_3	6.5897E-5	5.6875E-5	5.8816E-5
ξ_4	-2.0107E-4	-2.1472E-4	-2.1106E-4
λ	13.4558	13.7117	16.5558
β	0.0228	0.0485	0.0353
R_c	7.6505E-4	8.0000E-004	6.3813E-4
J_{max}	0.4690	1. 5000	0.4996
MAE	0.0530	0.1859	0.0506

5.3. Case of HeliocentrisFC-50

The data for this generator were obtained after implementing a series of experiments on the platform as depicted in Fig. 2. This PEMFC has 40W nominal power, with 10 cells connected in series. Cell area of 25 cm^2, and membrane thickness of 27 μm. The maximum operating temperature and anode pressure are 50 °C and 0.6 ±0.1 bars, respectively [59]. Moreover, the characterization process is conducted at the operating conditions of (P_a/P_c=0.60/0.90 bar, and T=26°C), (P_a/P_c=0.60/0.90 bar, and T=34 °C), and(P_a/P_c=0.60/0.90 bar, and T=46 °C). The first specified conditions were used to define the stack parameters, while the rest were kept for validation.

- **V/I characteristics**

The comparison of the simulation results between the proposed method and other competing approaches are summarized in Table 3. The best extracted parameters were fed into the model to predict (V/I) curves. Fig. 7-8 represent the (V/I) plots for all algorithms together with the experimental measurements. A very good matching is observed between the points predicted by the WOA and measurements across the entire-operating range. However, the estimations from the state-of-the-art methods show different degree of deviations as the magnified picture in Fig. 8 shows. The outcomes of the statistical measures in Table 4 confirm the validity of these observations. The proposed WOA has generated the least MAE and StE error values (*i.e.*, MAE=0.0506& StE=0.0969). ABC ranked second with values of MAE=0.0547 & StE=0.0996.PSO has ranked third (MAE=0.0551 & StE=0.1049), and DE was ranked last, with MAE = 0.0601 & StE = 0.1136. Moreover, from the statistical results, it can be viewed that the WOA and ABC exhibit the highest efficiency values in comparison to others, meaning that the named methods are more stable and robust compared to PSO and DE.

The excellent performance provided by the proposed WOA technique is due to its inherent exploration and exploitation mechanisms, which enable the distinction between-the global and local optimum values. In addition, the WOA algorithm spreads its individuals over the search space more intelligently, so that the probability of falling into one or more local optimums (LO) is significantly reduced. These features are not observed with other state-of-literature approaches. In fact, the literature methods have less flexibility and limited exploitative-exploratory capacities, which have resulted in LO stagnation occurrence, especially for DE technique.

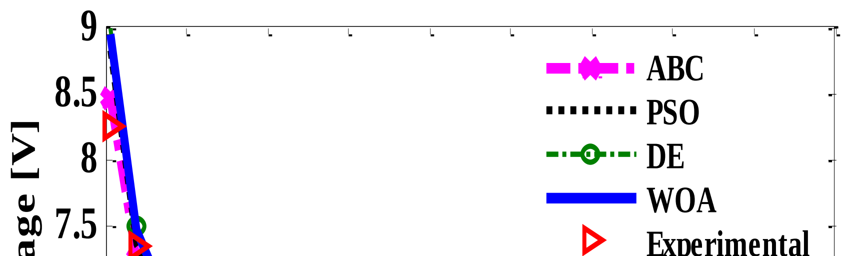

Fig. 7 – V/I characteristic at 26°C

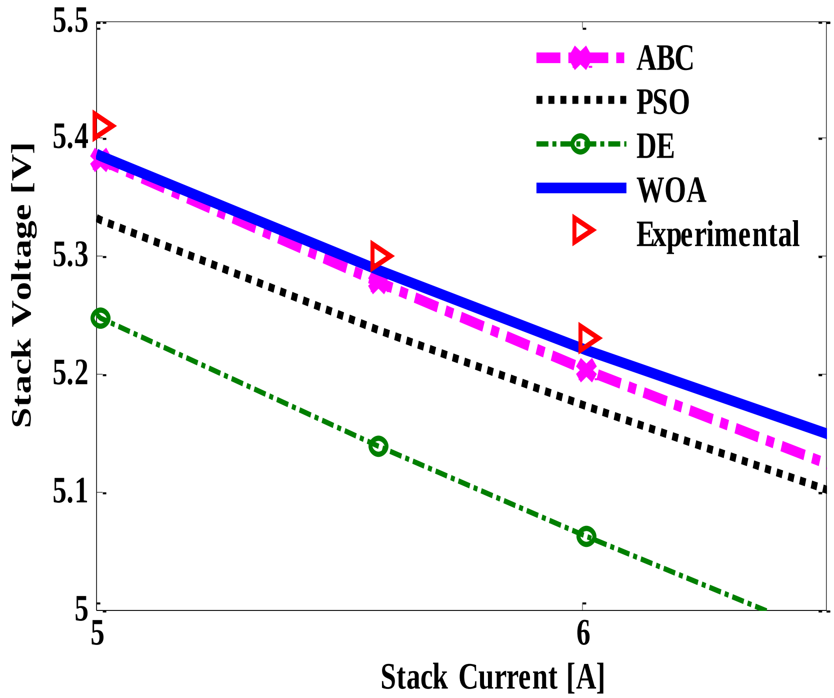

Fig. 8 – Magnified V/I curve

Table 3– Parameter fitting results for Heliocentris FC-50

Parameter	WOA	ABC	PSO	DE
ξ_1	-1.0837	-0.9776	-1.1624	-1.0659
ξ_2	0.0024	0.0017	0.0026	0.0025
ξ_3	5.8816E-5	3.6142E-5	5.6314E-5	7.2906E-5
ξ_4	-2.1106E-4	-2.0922E-4	-2.0806E-4	-2.0464E-4
λ	16.5558	15.6116	13.0530	13.0612
β	0.0353	0.0334	0.0403	0.0309
R_c	6.3813E-4	3.5027E-4	1.5794E-004	6.3562E-4
J_{max}	0.4996	0.4741	0.5000	0.4568
MAE	0.0506	0.0547	0.0551	0.0601
Iteration	119	234	276	309
Classification	1	2	3	4

- **Convergence speed**

The convergence speed of the suggested WOA algorithm in comparison to literature approaches is investigated in this section. Fig. 9 depicts the OF evolution versus the number of iterations, with a closer view illustrated in Fig. 10. It can observed from Fig. 9 that the WOA technique has the fastest-convergence-rate. The least value was reached in just a few iterations, which is 119th. The key behind gaining a rapid convergence characteristic by WOA is due to its unique search process, which seeks for the prey with more intensive exploration process at the beginning. After a while, the method exploits its remaining time in local search to improve the quality of the solutions. On the other-hand, the reason for the sluggish convergence in ABC & PSO is due to the repetitive LOs stagnation occurrence, which is very time consuming to ouvercom. To be more specific, ABC and PSO have stabilized after iterations number of 234 and 276, respectively.

With respect to DE method, it is hard to determine the key reason way it exhibits slow convergence behavior. One possible reason is that the DE generates individuals with heavy weights, which considerably slows down the population adjustment towards the target.

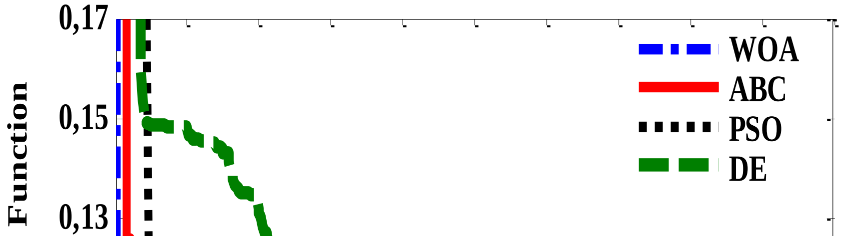

Fig. 9 – Convergence graph at steady-state

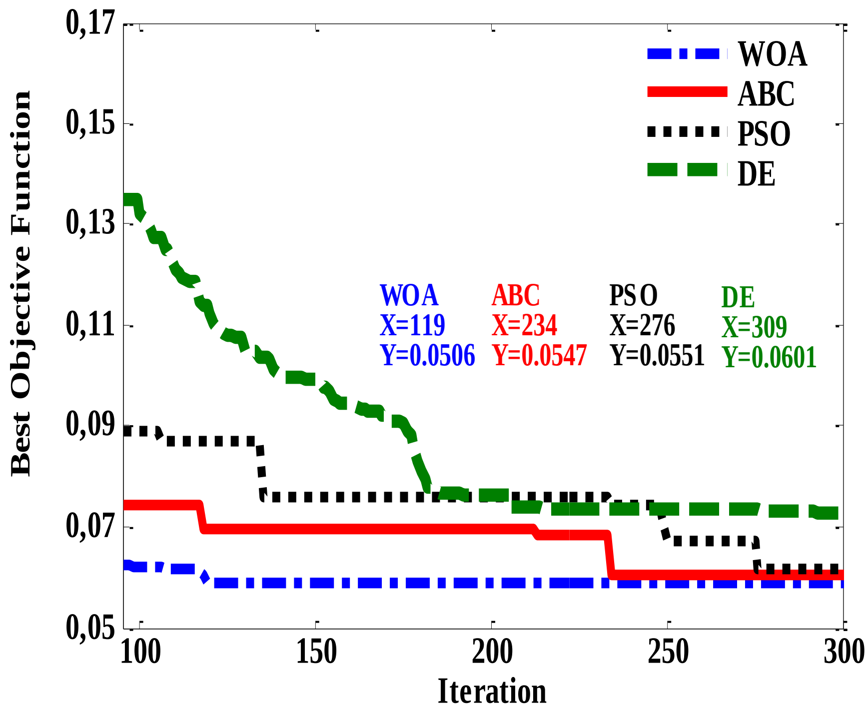

Fig. 10 – Magnified picture of convergence graph

- **Validation under varying operation conditions**

This section validates the adaptability of the WOA algorithm, and its ability in modeling the device characteristics under different operating conditions. The extracted optimal parameters are utilized to generate the (V/I) curves under the following operating conditions: (Pa/Pc= 0.33/0.42 bar, and T=34 °C) and (Pa/Pc= 0.41/0.62 bar, and T=46). The simulation outcomes of this test are displayed in Fig. 11. The results exhibit good accordance between-the true-and estimated data for both temperature values. The computed MAE values are as follows: 0.0704 V for T=46°C, and 0.0477 V for T=34°C. The above results fully demonstrate the validity and superiority of proposed method in enhancing the modeling of the PEMFCs, since the precision of the generated results is not only accurate at nominal conditions, but, also under different temperature levels.

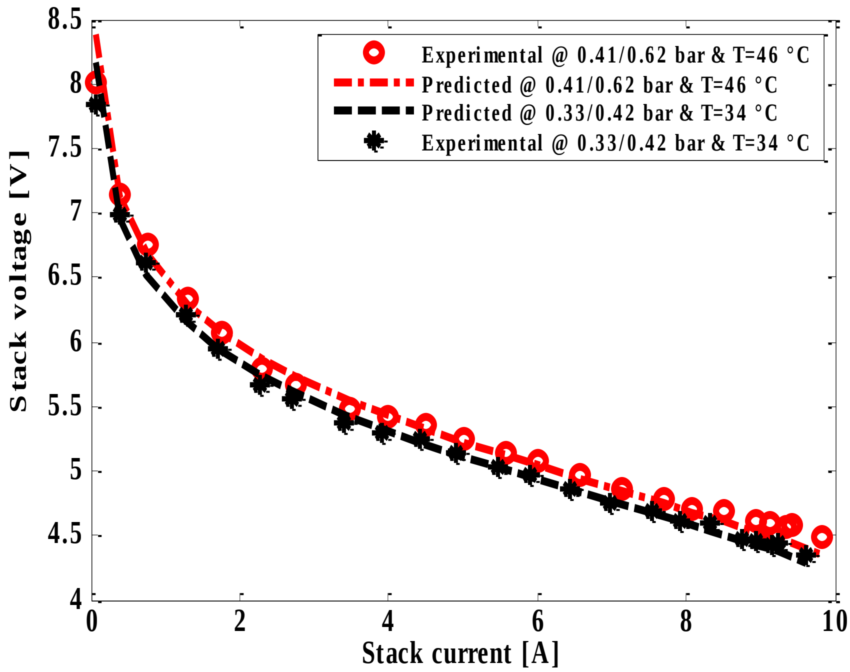

Fig. 11 – V/I curve under different operating conditions

6. Discussions

The simulation results for all case studies were subjected to some statistical benchmarks to measure the performance of the methods, as depicted in Table 4. From the tabulated results, it is noted that the outcomes of the proposed WOA outperform the results of the other models regarding accuracy as well as convergence property. The StE and η produced by the WOA confirm the stability of the method when solving such problems, since the most accurate parameters findings obtained by WOA. Based on statistical indicators displayed in Table 4, it can be seen that the second best result was achieved by ABC. While, PSO and DE were ranked third and fourth, respectively. Furthermore, the reader can notice that the outcomes of the proposed WOA are very close to those of the literature methods. However, a slight difference can significantly enhance the accuracy of the PEMFC model.

One noteworthy advantage of the WOA method is the effective time varying mechanism, which leads to a good balance between the exploration and exploitation phases. Such a feature is derived from the adaptive mechanism that control the adjustment of A coefficient. As long as ($|A| \geq 1$), the method forces itself to maximize the exploration process. While, if ($|A| < 1$) the method adjusts itself to exploit the discovered solutions and improve them more.

Furthermore, the non-linearity of objective function and the presence of the logarithmic term in the equations, may lead to potential local optimum stagnation. Consequently, the chance of getting trapped into one of the LOs grows. The proposed WOA optimization method alleviates this drawback by generating sufficient randomness so that all agents are distributed throughout the search space to avoid LOs, which is a feature that other benchmarks methods do not process.

With regards to the convergence speed, the simulation outcomes indicate that the WOA has the fastest convergence rate due to the light weight of the agents generated by the method. In contrast, the literature methods show some delay after reaching the minimum values. This slow convergence is also attributed to the local optimum stagnation behavior, where the agents need time to rectify there position and jump out of LO. Furthermore, to quantify the computational effectiveness of each method, the associated running time in seconds after 1000 iterations is measured, and presented in Table 4. There is a wide variation in the results of running time. There are a number of factors that govern the computational time like the number of (V/I) samples, and the number of variables. However, an important note that can be viewed is that the difference in running time between one method and the other is relatively small. Therefore, in cases where the computation time is a primer constraint to select an appropriate method, the choice becomes up to the designer to select any of these methods, since the difference between them is little, and changes according to the case study.

The above presented results and analysis demonstrated that the WOA method has superior performance compared to the state-of-literature meta-heuristic algorithms. Therefore, it can be stated that the WOA is a powerful optimization technique that can be adopted to establish high quality PEMFC model.

Table 4 – The outcomes of the statistical test

PEMFC	**BCS-500W**				**Ballard Mark V**				**Heliocentris-FC50**			
Indicator	**WOA**	**ABC**	**PSO**	**DE**	**WOA**	**ABC**	**PSO**	**DE**	**WOA**	**ABC**	**PSO**	**DE**
MAE	0.05300	0.0543	0.0544	0.0601	0.1859	0.1869	0.1862	0.1907	0.0506	0.0547	0.0551	0.0601
StE	0.0776	0.0888	0.0888	0.103	0.7279	0.8594	0.7013	0.7647	0.0969	0.0996	0.1049	0.1136
H	96.17	95.24	80.38	77.71	95.69	95.34	79.20	78.21	96.23	95.96	80.11	78.32
Running time in	1.5291	1.7950	1.6349	1.4453	1.4236	1.6259	1.6307	1.2713	1.1755	1.1819	1.1474	1.1705

sec												

7. Conclusion

In this study, the WOA algorithm has been proposed and applied to define the optimal of different PEMFC stacks. WOA has been proposed to improve the performance of the semi-empirical PEMFC model. A comprehensive statistical analysis has been done to confirm the stability, reliability and robustness of the proposed method. In addition, the optimization method have been employed to establish an accurate simulation model for Heliocentris fuel cell system installed LAGE laboratory, University of Ouargla. The simulation results proved that the WOA can improve the accuracy of the model by about 8.10%, with reference to second best result. In addition to the above-mentioned advantages, the WOA has demonstrated remarkable ameliorations in terms of convergence speed. The WOA technique has ranked first in majority of cases. Also, the efficacy of the established model by WOA was tested under varying temperature and oxygen/hydrogen pressures scenarios. The polarization curves obtained by the application of the proposed WOA method have revealed a good matching with the experimental curves measured under different operating conditions.

Based on the simulation outcomes, it has been observed that the proposed technique confirmed its reliability and efficiency in extracting the precise parameters of the PEMFC stack models compared with other literature algorithms. In the future study, the proposed algorithm can be used to solve other complex optimization problems like energy management of a hybrid system.

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Appendix 1: Controlling Coefficients.

Algorithm	**Controlling Coefficients**
DE	-Mutation scaling factor F= 0.8. -Crossover rate CR=0.9. -Donor is vector V is created by: -V=X_{rand_1}+ F× ($X_{rand\_2} - X_{rand\_3}$) -At every generation, the best solution is taken as the average-value-of the adapted population vector.
PSO	-Acceleration coefficients C_1=C_2=1.5. -Inertia weight ω=0.5;
ABC	-Employee bees are set equal to the half of population.

WOA	*b=1.*